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Return period of vegetation uprooting by flow

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Abstract

1 Fluvial environments are dynamic systems whose evolution and management
2 are strongly affected by the resilience of riparian vegetation to uprooting by
3 flow. Similarly to other natural phenomena, the interactions between flow,
4 sediment and vegetation uprooting is governed by both the magnitude and
5 duration of hydrological events. In this work, we analytically derive the link
6 between probabilities of plant uprooting by flow and the return time of corre-
7 sponding hydrologic erosion events. This physically-based analysis allows to
8 define the key parameters involved in the plant uprooting dynamics, and to
9 link the uprooting probability of riparian vegetation to plant biomechanical
10 characteristics, hydrological regime and sediment parameters. For example,
11 we show how the rooting depth changes the return time of critical hydrologic
12 event uprooting plants with different probabilities. The model also shows

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13 the difference between magnitude driven and duration driven flow uprooting
14 events. The proposed approach is eventually validated against data from field
15 measurements and numerical simulations of pioneer woody species for two
16 flood events with different return period. Our approach demonstrates the
17 strong interrelations between the hydrological river regime and vegetation
18 properties and suggests that such interactions may be key for species recruit-
19 ment and consequent ecosystem shifts when hydrological regime is altered by
20 either human or climate changing scenarios.

Keywords: Peak Over Threshold, Poisson process, flow erosion, plant
uprooting, type II uprooting

21 **1. Introduction**

22 Fluvial environments are dynamic systems whose evolution is governed
23 by the interactions between vegetation dynamics, sediment processes and
24 flow regime. Riparian plants alter turbulence structures, flow velocity and
25 sediment transport (Nepf, 2012b). At the same time, the alternation of low
26 and high flow discharges drives the recruitment, growth and decay of ripar-
27 ian vegetation (Edmaier et al., 2011). Particularly during high stage events,
28 vegetation is subjected to drag force and plant removal occurs when root
29 anchoring force is reduced through bed erosion to equal the drag (named

30 uprooting Type II after (Edmaier et al., 2011)). Vegetation uprooting un-
 31 der flow and scour constraints (Type II) was investigated by Edmaier et al.
 32 (2015) in laboratory experiments with *Avena sativa* and by Bywater-Reyes
 33 et al. (2015) in field measurements. Calvani et al. (2019a) used flume ex-
 34 periments with *Avena sativa* and *Salix purpurea* and field measurements to
 35 test and validate a model able to predict the critical bed erosion depth for
 36 which uprooting occurs. All these studies agree that the amount of bed
 37 erosion leading to plant uprooting by flow is smaller than the initial root-
 38 ing depth, thus supporting the critical rooting depth model (Edmaier et al.,
 39 2011; Calvani et al., 2019a). Perona and Crouzy (2018) hypothesized that
 40 for low plant size vs sediment size ratio, the critical rooting depth would
 41 correspond to a critical erosion depth. The latter is achieved by applying
 42 an erosion rate, which is the superposition of deterministic mean scouring
 43 (i.e., scouring happening over a characteristic longitudinal length scale) and
 44 random fluctuations mainly induced by turbulence and sediment transport
 45 mechanics.

46 Bed elevation changes, which include deposition and erosion, are regu-
 47 lated by the Exner equation, which states that time changing rate in bed ele-
 48 vation depends on the spatial variability of sediment fluxes. Specifically, in a

49 river reach, erosion takes place when downstream sediment outflow is larger
50 than the sediment inflow coming from upstream. Under a 1D framework, the
51 corresponding mathematical formulation is the 1D-Exner equation,

$$\frac{\partial \eta(x, t)}{\partial t} = -\frac{1}{(1 - \lambda_s) B} \frac{\partial Q_s}{\partial x} \quad (1)$$

52 where $\eta(x, t)$ is the bed elevation, x is the coordinate along the streamwise
53 direction of the main channel, t is time, λ_s is the sediment porosity, B is
54 the channel width and $Q_s(x, t)$ is the sediment discharge. At the time scale
55 of a single flood event, the difference in sediment transport fluxes between
56 two consecutive sections $\left(\Delta Q_s / \Delta x = \frac{1}{\Delta x} \int_1^2 dQ_s\right)$ is related to the bed shear
57 stress acting at the bottom of the channel, which depends on the average
58 flow velocity and, in turn, on the flow discharge. Therefore, the amount of
59 erosion achieved during a flood event depends both on the magnitude and
60 the duration of the event itself.

61 Flow discharge drives the uprooting process and, therefore, the hydrolog-
62 ical time scale of flood events governs the recruitment of riparian vegetation
63 species. Accordingly, riparian and aquatic species would have adapted their
64 biomechanical properties in order to withstand the flow regime and increase
65 survival chances during stress periods, due to either drought or flood events
66 (Karrenberg et al., 2002; Gibling and Davies, 2012; Gurnell, 2014). As a

67 result, the link between vegetation dynamics and hydromorphological time
 68 scales may represent the key factor to understand the biological evolution
 69 of riparian species and predict their effects on ecosystem dynamics (Calvani
 70 et al., 2019b). Such link was seldom investigated in literature, mostly by
 71 focusing on short time horizon only (Corenblit et al., 2015), although the
 72 interactions among native and invasive alien species and river morphody-
 73 namics employ decades to evolve (Habersack, 2000; Solari et al., 2016). To
 74 this purpose, an analysis on the long term (return period) is therefore sought,
 75 as well as the definition of an hydrograph associated to such return period.
 76 This is particularly required when both the magnitude and the duration of
 77 the flow event play a fundamental role in flow-time related processes, such
 78 as flood risk modelling and management (e.g., Mignot et al., 2018; Tanaka
 79 et al., 2017), dam overtopping (e.g., Schmocker and Hager, 2009) and sedi-
 80 ment transport (e.g., Powell et al., 2001), among others.

81 In this work we link the uprooting probability P_τ to the extreme value
 82 analysis of a flow discharge Compound Poisson Process (CPP) using the
 83 Peak Over Threshold (POT) methodology. POT is a common mathematical
 84 approach to evaluate the occurrence probability (i.e., return period) of rare
 85 extreme events and is widely used in many disciplines, such as meteorol-

ogy, geological, hydraulic and structural engineering and earth sciences (e.g.,
 Leadbetter, 1991; Önöz and Bayazit, 2001; Novak, 2011; Castillo, 2012). We
 additionally provide a formulation for the statistically average hydrograph
 of a flow event associated to such threshold and its return period. We then
 apply the proposed formulation to the case study of vegetation removal by
 flow and bed erosion (Type II uprooting). We combine the POT of the CPP
 and the probabilistic model of plant removal to correlate the hydrological
 parameters to the return period of riparian vegetation uprooting probability.
 As last, we perform a sensitivity analysis on the parameters involved and test
 the proposed approach against field measurements data from Bywater-Reyes
 et al. (2015).

2. Methodology

2.1. The uprooting model

Consider figure 1, which represents the uprooting process investigated by
 Perona and Crouzy (2018). Scouring trajectories originate from the initial
 bed level ($\eta = 0$), reduce plant anchoring, until the critical erosion depth (i.e.,
 $\eta = -L_e$) is achieved, then plant is uprooted. The different trajectories evolve
 according to the flow hydrograph $Q_\xi(t)$ and the stochasticity in the erosion

process, g_t . Such process results in a probability distribution function, $p_\tau(t)$, of the times leading to uprooting. According to Perona and Crouzy (2018), the probability distribution function of time to uprooting, $p_\tau(t)$, reads:

$$p_\tau(t) = \frac{L_e}{2\sqrt{\pi} G^3(t)} \left(\frac{g_t(t)}{2} \text{Exp} \left[-\frac{(L_e - V(t))^2}{4 G(t)} \right] + W(t) \text{Exp} \left[\frac{L_e V(t)}{G(t)} \right] \right) \quad (2)$$

where L_e is the critical erosion depth for plant uprooting to occur, $g_t(t)$ describes the strength of uncorrelated Gaussian noise of the erosion process, $G(t) = \frac{1}{2} \int_0^t g_t(\tau) d\tau$, $V(t) = \int_0^t \dot{L}_d(\tau) d\tau$ and $W(t) = \sqrt{\pi G(t)} \text{Erfc} \left[\frac{L_e + V(t)}{2 \sqrt{G(t)}} \right] \left(\dot{L}_d(t) - \frac{g_t(t)}{2} \frac{V(t)}{G(t)} \right)$, with τ the dummy time variable of integration. Therein, the deterministic part of the root exposing rate due to bed erosion is $\dot{L}_d = \dot{\eta}_d(t) dL/d\bar{\eta}$ where $dL/d\bar{\eta}$ accounts for the root shape and architecture within the soil. We assume $dL/d\bar{\eta} = 1$ under the simplifying hypothesis of root vertical development (Edmaier et al., 2015; Calvani et al., 2019a). This requires that the average hydrograph of an event must be defined in order to calculate the associated erosion rate, its total duration \hat{T}_ξ (figure 1) and the correspondent uprooting probability $P_\tau(t = \hat{T}_\xi)$.

The quantity g_t has the unit of a diffusivity (i.e., $\text{m}^2 \text{s}^{-1}$) and models the stochasticity of turbulence and sediment transport mechanics. Since no

120 formulation are available in literature, we argue that a relationship for the
 121 quantity g_t can be sought in the formula of the eddy viscosity (Pope, 2001;
 122 Michael, 2015), as disturbances in sediment transport are directly related to
 123 fluid obstacle interactions and flow turbulence at the stem scale (Nepf, 2012a;
 124 Perona and Crouzy, 2018). Thus, the formula reads:

$$g_t(t) = l_s \cdot u_* \quad (3)$$

125 where l_s is the *sediment mixing length* (i.e., a length scale along the vertical
 126 direction y) and u_* is the shear velocity, that plays the role of a velocity scale
 127 along the longitudinal direction x , similarly to the case of eddy viscosity ν_t .
 128 We set the sediment mixing length l_s equal to the mobilized sediment layer
 129 thickness, which is in the order of magnitude of the D_{90} . Accordingly, the
 130 equation for l_s reads

$$l_s = k_g \cdot D_{90} \quad (4)$$

131 where k_g is a multiplying coefficient equal to 2, according to Parker (1990).
 132 For the sake of dimensional consistency in unit of measurement, a multiplying
 133 constant equal to 1 s d^{-1} has to be taken into account when considering the
 134 strength of the Wiener process (see Eq. (2.10) in Perona and Crouzy (2018)).

135 Finally, the relationship for the probability of Type II uprooting $P_\tau(t)$

reads (Perona and Crouzy, 2018):

$$P_{\tau}(t) = \int_0^t p_{\tau}(\tau) d\tau \quad (5)$$

2.2. Peak Over Threshold analysis

We now approximate the flow discharge signal to a Compound Poisson Process. The Compound Poisson Process (CPP) is a common mathematical representation to describe the dynamics of stochastic systems where instantaneous perturbations cause sudden jumps in the state variable (Cox and Miller, 1965; Ridolfi et al., 2011). Forest fire spread (Daly and Porporato, 2006; Zen et al., 2018), avalanches induced by snowfall (Perona et al., 2007, 2012), groundwater recharge, soil moisture increase (Rodriguez-Iturbe et al., 1999; Botter et al., 2007), river flood events due to heavy rainfall (Todorovic, 1978; Önöz and Bayazit, 2001; Lague, 2010) and ecomorphodynamics (Crouzy and Perona, 2012; Bertagni et al., 2018) are only some of the natural processes that can be modelled using the CPP approach. In the following, we focus on flow discharges in a straight channel, characterized by constant width and bed slope. We assume flow discharge $q(t)$ being driven by a deterministic drift (i.e., exponential decrease $\text{Exp}[-t/\tau_P]$, with decay rate τ_P)

153 and instantaneous random positive jumps (with average frequency λ_P) rep-
 154 resenting the flood events (figure 2) (Botter et al., 2007). The average flow
 155 discharge μ_P of the CPP is $\mu_P = \gamma_P \cdot \lambda_P \cdot \tau_P$, where γ_P is the mean values
 156 of the jumps. Accordingly, flow discharge can be modelled by a probabilistic
 157 distribution function, $p(q)$ (figure 2), of the form (Lague et al., 2005; Botter
 158 et al., 2007):

$$p(q) = \frac{1}{q \Gamma(\beta_P)} \text{Exp} \left[-\frac{q}{\gamma_P} \right] \left(\frac{q}{\gamma_P} \right)^{\beta_P} \quad (6)$$

159 where $\Gamma[\beta_P]$ is the complete Gamma function (Abramowitz and Stegun, 1965)
 160 with $\beta_P = \lambda_P \tau_P$.

161 Next, we perform an extreme value analysis using the Peak Over Thresh-
 162 old (POT) approach developed by Todorovic (1970) and then applied to
 163 exponentially distributed peak events (CPP) by Zelenhasic (1970) and Önöz
 164 and Bayazit (2001), among others. Once a certain threshold ξ is set, POT al-
 165 lows to evaluate the return period $T(\xi)$ of the flow discharge higher than such
 166 threshold. For the sake of brevity, only the main results are reported here
 167 below, whereas we address the reader to Calvani (2019) for the calculation
 168 steps. The return period $T(\xi)$ simply reads:

$$T(\xi) = \frac{1}{1 - P_\xi} \quad (7)$$

169 Therein, the probability of events higher than the threshold ξ , P_ξ as given

170 by the POT analysis, is equal to:

$$P_{\xi} = e^{-T \lambda_P P_{\xi}^+} \quad (8)$$

171 where T is a temporal quantity set equal to 1d for the aim of the POT,
 172 $\lambda_P' = \frac{e^{-\phi} \phi^{\beta_P}}{\tau_P \Gamma[\beta_P]}$ is the average frequency of upcrossing the threshold ξ ; ϕ is the
 173 ratio between the threshold ξ and the mean value of pulses γ_P ; P_{ξ}^+ is the
 174 probability of the signal $q(t)$ (figure 2) to be higher than the threshold ξ ,
 175 that is $P_{\xi}^+ = \int_{\xi}^{\infty} p(q) dq = \frac{\Gamma[\beta_P, \phi]}{\Gamma[\beta_P]}$ (Ridolfi et al., 2011) where $\Gamma[\beta_P, \phi]$ is the
 176 upper incomplete Gamma function (Abramowitz and Stegun, 1965). It must
 177 be clear that the two frequencies, λ_P and λ_P' , represent different quantities
 178 for the CPP. The first one, λ_P , is a property of the process and depends, in
 179 this case, on the hydrological regime of the river, only. On the contrary, the
 180 second one, λ_P' , depends on the threshold value, ξ . To clarify this point, one
 181 can compare the whole number of jumps in figure 2 (which depends on λ_P)
 182 to the number of jumps across above the threshold ξ (which depends on λ_P').

183 2.3. Reference mean event

184 For a given threshold ξ and its return period $T(\xi)$ (Eq. (7)), we calculate
 185 the associated reference mean event, which represents a statistically averaged
 186 flow hydrograph following a jump (peak) above the threshold ξ and lasts

187 until downcrossing the threshold Q_{cr} . As we focus on events able to uproot
 188 vegetation after riverbed erosion (i.e., Type II uprooting), we consider flow
 189 discharge above the threshold value for incipient motion of sediment Q_{cr} only,
 190 which we assume equal to the one for the incipient erosion. Such value can
 191 be calculated as follows:

$$Q_{cr} = \tau_{cr}^{*5/3} \left(\frac{\rho_s - \rho}{\rho} \right)^{5/3} D_{50}^{5/3} \frac{B}{n} S^{-7/6} \quad (9)$$

192 where τ_{cr}^* is the critical Shields parameter equal to either 0.03, according to
 193 Parker et al. (2007) for gravel bed rivers subjected to bedload transport, or
 194 τ_{SL}^* for sand-bed rivers with suspended load; ρ_s and ρ are sediment and water
 195 density, respectively; D_{50} is the mean grain size; B is the river width; n is the
 196 Manning coefficient and S is the bed slope. The critical Shields parameter for
 197 sand-bed rivers τ_{SL}^* can be calculated using Brownlie's equation (Brownlie,
 198 1981).

199 We address the reader to Calvani (2019) for the whole mathematical
 200 approach and report here the final equation of the reference mean event
 201 $Q_\xi(t)$ defined by a piecewise function:

$$Q_\xi(t) = \begin{cases} Q_0(\xi) e^{-t/\tau_1} & [0 \leq t \leq T_\xi^+] \\ \xi e^{-(t-T_\xi^+)/\tau_2} & [T_\xi^+ < t \leq \hat{T}_\xi] \end{cases} \quad (10)$$

202 Quantities $Q_0(\xi)$, τ_1 and τ_2 are calculated according to the properties of
 203 the Compound Poisson Process: particularly, the average time, T_ξ^+ , and the
 204 average flow value, $\bar{Q}_{q>\xi}$, above the threshold ξ , and the average time, $T_{\xi \rightarrow Q_{cr}}$,
 205 from the threshold ξ to the threshold Q_{cr} . The temporal quantities, T_ξ^+ and
 206 $T_{\xi \rightarrow Q_{cr}}$, are related to the concept of mean first passage time, that is the
 207 average time that a signal upcrosses or downcrosses a certain threshold value
 208 (Laio et al., 2001; Ridolfi et al., 2011). The total duration of the reference
 209 mean event is, therefore:

$$\hat{T}_\xi = T_\xi^+ + T_{\xi \rightarrow Q_{cr}} \quad (11)$$

210 To this regard, we must point out that flow volume conservation is exactly
 211 satisfied for the first part of the reference mean event only (i.e., from Q_0 to
 212 ξ), as this is imposed using the conditions for T_ξ^+ and $\bar{Q}_{q>\xi}$. The second ex-
 213 ponential decay (i.e., from ξ to Q_{cr}) is calculated using the exact formulation
 214 for the average time $T_{\xi \rightarrow Q_{cr}}$. This may lead to error in the flow volume con-
 215 servation, and the outcomes of this assumption will be explored in Section
 216 3.1.

217 2.4. Erosion rate

218 In order to account for bed elevation changes and scouring events promot-
219 ing Type II uprooting during high flow events, we couple the time-varying
220 flow discharge to the 1D Exner (Eq. (1)) and sediment transport relation-
221 ships. For the sediment transport, we consider both the cases of bed and
222 suspended load. Specifically, we assume a Meyer-Peter-Müller type formula
223 (Wong and Parker, 2006) for bedload and the van Rijn’s model (van Rijn,
224 1984) for the suspended load. For the resultant relationships to be as simple
225 as possible, we neglect the effects of the time derivative in the momentum
226 equation at the time scale of the process. As a result, bed shear stress τ_b
227 and water depth Y can be calculated from flow discharge only, by know-
228 ing channel geometry and involving the Manning relation for normal flow.
229 Additionally, for the channel geometry, we assume a wide rectangular cross-
230 section with constant width and bed slope. By combining the aforementioned
231 formulas and assuming negligible upstream sediment discharge (Perona and
232 Crouzy, 2018), we obtain a relationship for the net (deterministic) erosion
233 rate $\dot{\eta}_d$ where the typical structure of sediment transport formula above crit-
234 ical threshold and exponent 3/5 coming from Manning relation can be rec-

235 ognized. The relation reads:

$$\dot{\eta}_d(t) = \psi_1 \psi_2 \left(q^{\frac{3}{5}}(t) - Q_{cr}^{\frac{3}{5}} \right)^b \cdot \left(q^{\frac{3}{10}}(t) \cdot I(q(t), D_{50}) \right)^{a_{ST}} \quad (12)$$

236 where ψ_1 is a coefficient depending on physical parameters, river size and
 237 sediment properties, ψ_2 is a coefficient depending on the main type of sedi-
 238 ment load, b is the exponent in the sediment transport formula (e.g., $3/2$ in
 239 the case of van Rijn's and MPM's models), $I(q(t), D_{50})$ is a quantity given
 240 by the Einstein's integrals (Einstein, 1950) and depending on mean grain
 241 size D_{50} and flow discharge in the case of suspended load only, and a_{ST} is a
 242 parameter equal to either 0 for bedload or 1 for suspended load. The relation
 243 for the parameter ψ_1 reads:

$$\psi_1 = \frac{\sqrt{g} D_{50}^{1-b}}{(1 - \lambda_s) \Delta x} \left(\frac{\rho_s - \rho}{\rho} \right)^{-b} \left(\frac{n}{B} \right)^{\frac{3}{5}b} S_{10}^{\frac{7}{10}b} \quad (13)$$

244 where g is the acceleration due to gravity, λ_s is the sediment porosity, Δx is
 245 the length scale along the streamwise direction where the spatial derivative of
 246 sediment transport (right-hand side term in Eq. (1)) can be approximated by
 247 the finite difference. Following the approximation suggested by Perona and
 248 Crouzy (2018), Δx is the spatial scale, where net (parallel) bed erosion takes
 249 place. The coefficient ψ_2 depends on the main type of sediment transport,

250 according to the following relation:

$$\psi_2 = \begin{cases} \alpha_{BL} D_{50}^{1/2} \left(\frac{\rho_s - \rho}{\rho} \right)^{\frac{1}{2}} & a_{ST} = 0 \\ \alpha_{SL} \left(\frac{n}{B} \right)^{\frac{3}{10}} S^{\frac{7}{20}} R_{ep}^{-\frac{2}{10}} \tau_{SL}^{*b} & a_{ST} = 1 \end{cases} \quad (14)$$

251 Therein, α_{BL} is the coefficient in the bedload formula (e.g., 3.97 in Wong
 252 and Parker (2006)), $\alpha_{SL} = 0.174$ is the coefficient in van Rijn's formula for
 253 suspended load (van Rijn, 1984) and R_{ep} is the particle Reynolds number.
 254 It is worth to mention that, in the case of bedload ($a_{ST}=0$ in Eq. (14)),
 255 when $b=1.5$ (e.g., Meyer-Peter and Müller, 1948; Wong and Parker, 2006),
 256 the mean grain size D_{50} cancels out in the product $\psi_1 \cdot \psi_2$ in Eq. (12). As
 257 a result, the erosion rate $\dot{\eta}_d(t)$ depends on the mean grain size, D_{50} , by the
 258 critical flow for incipient motion of sediment, Q_{cr} (Eq. (9)), only.

259 3. Results

260 3.1. Reference mean event

261 A graphical explanation of the reference mean event $Q_\xi(t)$ (Eq. (10))
 262 is reported in figure 3a), with the associated erosion rates due to bedload
 263 and suspended load and the critical thresholds, Q_{cr} , for incipient sediment
 264 transport (Eq. (9)). Figure 3b) shows the comparison between a reference

mean event (blue line) and some Compound Poisson Process events (thin black lines) between the two thresholds ξ and Q_{cr} .

Due to assumptions made in the calculations of the reference event (Eq. (10)), particularly the second exponential decay from ξ to Q_{cr} (Section 2.3), we compared the flow volume of the reference mean event (i.e., $\int_0^{\hat{T}_\xi} Q_\xi(t) dt$) to the average flow volume of some events taken from a CPP, according to various combinations of the parameters λ_P and τ_P , and with respect to different values of the threshold ξ . The comparison was carried out for two ideal rivers characterized by different hydro-morphological parameters. The first one, here named the *Small River*, has a cross section width, B , equal to 50m, bed slope, S , equal to 0.005, and grain size distribution characterized by D_{50} equal to 0.1m and D_{90} equal to 0.15m. The corresponding hydrology is characterized by a mean flow discharge, μ_P , equal to $15\text{m}^3\text{s}^{-1}$, average frequency of events, λ_P , equal to 0.1d^{-1} , and exponential decay rate, τ_P , equal to 1.5d. The second river, here named the *Large River*, has a cross section width, B , equal to 100m, bed slope, S , equal to 0.002, and grain size distribution characterized by D_{50} equal to 0.04m and D_{90} equal to 0.1m. The corresponding hydrology is characterized by a mean flow discharge, μ_P , equal to $400\text{m}^3\text{s}^{-1}$, average frequency of events, λ_P , equal to 0.1d^{-1} , and

284 exponential decay rate, τ_P , equal to 1.5d. For both the rivers, the D_{90}
 285 was used to calculate the Manning coefficient n , according to the empirical
 286 relation $n = D_{90}^{1/6}/26$. The results of the comparison are shown in figure 4.

287 The comparison shows that, as expected, the formulation of the reference
 288 mean event (Eq. (10)) does not capture exactly the average flow volume dur-
 289 ing the exponential decay from the upper threshold ξ to the lower threshold
 290 Q_{cr} . Nevertheless, the agreement seems satisfactorily as the relative error is
 291 overall less than 5%, with a maximum of 15% for some very particular com-
 292 binations of the parameters λ_P and τ_P (e.g., $\lambda_P=0.02\text{d}^{-1}$ and $\tau_P=7\text{d}$) which
 293 are uncommon in natural rivers. It is worth to note that the flow volume
 294 calculated using the reference mean event overestimates the numerical data
 295 for most of the λ_P - τ_P combinations in the Small River. On the contrary, it
 296 has the tendency to underestimate the numerical data in the Large River.
 297 As a result, the formulation of the reference mean event yields to predicting
 298 errors in the uprooting probability. To this regard, we compared the average
 299 uprooting probability of fifty events taken from a CPP with two different val-
 300 ues of the higher threshold ξ for the Small River and the Large River (figure
 301 3c,d). For the Small River, for the first value of the threshold, $\xi=125\text{m}^3\text{s}^{-1}$,
 302 the average uprooting probability of the CPP events was $P_\tau=0.24$, whereas

303 the uprooting probability calculated using the corresponding reference mean
 304 event was $P_\tau(t = \hat{T}_\xi)=0.32$. For the second threshold value, $\xi=180\text{m}^3\text{s}^{-1}$
 305 (figure 3c), the uprooting probability from the CPP was $P_\tau=0.24$, whereas
 306 $P_\tau(t = \hat{T}_\xi)=0.56$. For the Large River, the first threshold value was set to
 307 $\xi=550\text{m}^3\text{s}^{-1}$ and the uprooting probability of the CPP events was $P_\tau=0.53$,
 308 with the corresponding $P_\tau(t = \hat{T}_\xi)$ of the reference mean event equal to 0.54
 309 (figure 3d). For the second value of the threshold, $\xi=750\text{m}^3\text{s}^{-1}$, the uproot-
 310 ing probabilities were $P_\tau=0.58$ and $P_\tau(t = \hat{T}_\xi)=0.55$. As a consequence of the
 311 approximation of the flow volume (figure 4), the approach leads to slight un-
 312 derestimations of the uprooting probability in the case of the Large River and
 313 overestimations in the case of the Small River. Therefore, we are confident
 314 that the case of $\xi=550\text{m}^3\text{s}^{-1}$ in the Large River with slight overestimation of
 315 the uprooting probability depends on the particular randomly chosen events
 316 that are mainly lying below the reference mean event (see figure 3d).

317 3.2. Resilience to vegetation uprooting

318 We performed the calculations of $P_\tau(t = \hat{T}_\xi)$ for both the rivers presented
 319 in the previous section, in the case of bedload transport (i.e., $\alpha_{ST}=0$ in Eq.
 320 (14)). For the sake of simplicity, we did not consider the case of suspended
 321 load (i.e., $\alpha_{ST}=1$ in Eq. (14)), even when the Shields number would be

322 large enough to support its occurrence at high value of the flow discharge.
 323 The length scale, Δx in Eq. (13), was set equal to $6 \cdot B$, which is roughly the
 324 length scale of potential river bars (Leopold and Wolman, 1957). Due to the
 325 highly non-linear relationships involved in the calculation of the uprooting
 326 probability $P_\tau(t = \hat{T}_\xi)$, we performed a graphical analysis on the effects of
 327 varying parameter values, one at a time. In particular, we considered the
 328 effects of the critical erosion for uprooting, L_e and the coefficient α_{BL} in bed
 329 load sediment transport formula, by accounting for constant values of the
 330 hydrological parameters, μ_P , λ_P and τ_P . Additionally, we kept constant the
 331 fluctuations of the sediment transport rate ($g_t = 0.05 \text{ m}^2 \text{ d}^{-1}$), regardless of
 332 Eq. (3), to highlight the changes induced by varying the tested parameter.
 333 Figure 5 shows the trend of the uprooting probability function, $P_\tau(t = \hat{T}_\xi)$,
 334 versus the corresponding return period T_ξ at varying the parameters, for the
 335 Small River and the Large River, respectively.

336 For both rivers, the critical erosion depth L_e plays an important role in
 337 the probability of uprooting. In case of the Small River, figure 5a) shows
 338 that an increment of 0.25m in L_e (e.g., from 0.5m to 0.75m) raises survival
 339 chances ($= 1 - P_\tau$) by more than 30% for a yearly flow event. For the Large
 340 River (figure 5c), the same consideration implies an increment of 20% in the

survival chances. According to Calvani et al. (2019a), plants do not need
 to grow root as deep as that amount, as soil strength increases with depth.
 Furthermore, the same gain in L_e can be achieved by reducing the frontal
 area subjected to drag, either by increasing flexibility (i.e., reconfiguration)
 or by physically losing leaves. The latter mechanism appears to be a possible
 strategy for riparian plants in the temperate zone to adapt their deciduous
 period to autumn and winter seasons, not only to save energy, but also to
 withstand the larger and more frequent peak events.

For the effects of the coefficient of the bedload transport formula, we
 considered the original value proposed by Wong and Parker (2006) and four
 other values, differing by $\pm 25\%$ and $\pm 50\%$. For the Large River, figure 5d)
 shows that increasing the coefficient α_{BL} by 25% raises the uprooting prob-
 ability by roughly 5% in the whole range of the tested return periods. A
 similar behaviour in the function P_τ can be observed when the coefficient
 α_{BL} decreases by 25% ($\alpha_{BL}=2.978$). In this case we observed a decrease in
 the uprooting probability by 5%, only. As a result, the parameter α_{BL} in
 the range of tested values does not seem to significantly affect the uproot-
 ing probability. Different results were obtained for the Small River, where
 the variation imposed in the bedload transport coefficient, α_{BL} , affect the

360 uprooting probability by more than 10% for a yearly flow event (figure 5b).
361 Particularly, for the case of doubling the bedload transport coefficient, the
362 uprooting probability increases by 25%.

363 Additionally, we investigated the effects of varying the hydrological pa-
364 rameters, specifically the average jump value γ_P , the average frequency of
365 jumps λ_P , and the exponential decay rate τ_P , and the grain size distribution,
366 with particular focus on the mean grain size D_{50} . The results of the analysis
367 are reported in figures 6 and 7, for the Small River and the Large River,
368 respectively.

369 Both rivers show similar trends of the uprooting probability, while varying
370 the same parameter. Similarly to the case with constant mean flow discharge
371 μ_P (figure 5), the influence of the investigated parameters is more evident in
372 the Small River, when compared to the Large River. Such result is partic-
373 ularly clear in figures 6 and 7 when comparing panels c), varying the mean
374 value of jump, γ_P , and panels d), at varying the mean grain size D_{50} .

375 Consider now, the case of figure 8, where the uprooting probabilities of
376 two different cross sections in the same river are shown. Hydro-morphological
377 parameters are representative of the Thur River (CH), at the two measuring
378 stations of Jonschwil, Mühlau (upstream) and Andelfingen (downstream).

379 Data are reported within the figure. The uprooting probability $P_\tau(t = \hat{T}_\xi)$,
 380 for the same critical erosion length ($L_e=0.75\text{m}$) and erosion process noise
 381 ($g_t=0.05\text{m}^2\text{d}^{-1}$), shows the existence of a return period for which the two
 382 curves intersect. Such return period corresponds to equal uprooting prob-
 383 ability in both the cross sections, thus supporting the idea of selecting the
 384 survival of equal vegetation species along the whole river reach. We explain
 385 this trend by considering the different reference mean events and the associ-
 386 ated p_τ obtained for the tow different cross sections. For low return periods
 387 (e.g., $T(\xi) \approx 0.3\text{y}$), the uprooting probability is higher in the downstream
 388 cross section (DS). The main reason is the longer duration of the reference
 389 mean event for the DS cross section, if compared to that in the upstream
 390 (US) one (i.e., $\hat{T}_\xi^{DS} > \hat{T}_\xi^{US}$). On the contrary, for higher return periods (e.g.,
 391 $T(\xi) \approx 10\text{y}$), the uprooting probability is higher in the US cross section. Al-
 392 though the condition $\hat{T}_\xi^{DS} > \hat{T}_\xi^{US}$ still applies, the probability distribution
 393 function, p_τ , in case of the US cross section (see bottom-left inset panel in
 394 figure 8) shows a very remarkable peak, leading to a higher integral value, P_τ .
 395 We refer to this dualism as *duration driven* and *magnitude driven* uprooting
 396 events, respectively.

397 3.3. Real case application

398 We applied the proposed methodology and the uprooting model to the
399 case study of the Santa Maria River (Arizona, USA). This river was inves-
400 tigated by Bywater-Reyes et al. (2015) and plants on a bar along it were
401 mechanically uprooted under different conditions of scouring. As a results,
402 data of flow discharge to fit the CPP and measurements of root resistance
403 and plant geometry are both available.

404 Figure 9a) shows the reference mean event and its associated erosion rate
405 $\dot{\eta}$ driven by suspended load ($a_{ST}=1$ in Eq. (12)) for the 10y return period
406 peak event. We calculated the uprooting probability according to different
407 critical erosion length L_e and compared the results for the two flow discharges
408 investigated by Bywater-Reyes et al. (2015) ($Q_2=80\text{m}^3\text{s}^{-1}$; $Q_{10}=460\text{m}^3\text{s}^{-1}$)
409 and the plants uprooted under 0.30m scouring condition. For the measured
410 plants, we calculated the minimum, median and maximum of uprooting prob-
411 ability of according to the corresponding velocities as output numerical sim-
412 ulation carried out by Bywater-Reyes et al. (2015) for the two investigated
413 return periods. Figure 9b) shows the uprooting probability $P_\tau(t = \hat{T}_\xi)$ versus
414 the threshold ξ for different values of the unknown variable L_e for the Santa
415 Maria River. The critical erosion length $L_e = 0.33\text{m}$ used in figure 9b) was

416 calculated according to the model proposed by Calvani et al. (2019a) for the
 417 mechanically uprooted plants for which measurements of intact root (i.e.,
 418 main root length) were available. Uprooting probability for measured plants
 419 are shown as boxplots. As a final result of our analysis, we found a very good
 420 agreement between measured and modelled uprooting probability for both
 421 the flow discharges. Therefore, this supports the validity of our analysis and
 422 the robustness of our approach.

423 **4. Discussion**

424 For the sake of clarity, we have considered the reference mean event
 425 $Q_\xi(t)$ starting when a jump in the Compound Poisson Process up-crosses
 426 the threshold ξ . This is replicated in the reference mean event by the initial
 427 jump from the critical value Q_{cr} to the the flow discharge $Q_0(\xi)$. This as-
 428 sumption is often legitimated by the generally shorter duration of the raising
 429 limb compared to that of the falling limb in a flow hydrograph. However, such
 430 hypothesis can not be satisfied in case of high correlated signals, for instance
 431 when the temporal scale τ_P governing the exponential decrease (deterministic
 432 drift in the CPP) is larger than the average interval between shots (i.e., λ_P^{-1}).
 433 In this case, a more appropriate formulation for the raising limb of the refer-

434 ence mean event must be provided. This is object of ongoing investigations.
 435 Nevertheless, hydrological regimes with such characteristics are uncommon
 436 so we are confident that the proposed formulation and methodology can be
 437 satisfactorily applied to most rivers (e.g., figure 9).

438 Additionally, in this section, we focused on Eq. (3) and the associated
 439 time-varying g_t . We investigated the effects of different values of k_g (Eq.
 440 (4)), representing the variability of the mobilized sediment layer thickness.
 441 We compared the resulting uprooting probabilities with constant and time-
 442 varying g_t . For the sake of the analysis, we consider the constant g_t as the
 443 integral average of the time-varying one over the entire duration \hat{T}_ξ of the
 444 reference mean event $Q_\xi(t)$ for a given return period $T(\xi)$.

445 Figure 10 shows the comparison among uprooting probabilities with con-
 446 stant and time-varying g_t according to different values of k_g . Time-varying
 447 g_t plays a significant role in modifying the resultant $P_\tau(t = \hat{T}_\xi)$ only for ei-
 448 ther very high or very low values of k_g (e.g., $k_g = 0.2$ or $k_g = 20$). For more
 449 reasonable values (e.g., $k_g = 2$ (Parker, 1990)), the uprooting probabilities
 450 are very similar and, therefore, the average value defines the entire trend.
 451 This behaviour is clearly explained by the corresponding probability distri-
 452 bution functions, p_τ , plotted in the inset panels of figure 10 for two different

453 return periods, $T(\xi)$. Moreover, for values of k_g equal to 4, time-varying g_t
 454 increases the uprooting probability for low return periods (e.g., $T(\xi) < 11\text{y}$),
 455 whereas $P_\tau(t = \hat{T}_\xi)$ is almost equal for slightly higher recurrence intervals
 456 (e.g., $10\text{y} < T(\xi) < 50\text{y}$). For higher return period ($T(\xi) > 50\text{y}$), the up-
 457 rooting probability with the time-varying g_t is lower than the correspondent
 458 with constant g_t . For even higher values ($k_g = 20$), the uprooting probability
 459 with time-varying g_t is always larger, for the tested range of return period
 460 and hydrological parameters. It is interesting to highlight that for k_g lower
 461 than 4, the uprooting probability function behaves in the opposite way. We
 462 didn't investigate on the threshold value of k_g that switches between the two
 463 different trends.

464 5. Conclusions

465 In this work, we linked the uprooting probability given by the stochastic
 466 model of Perona and Crouzy (2018) to the return period of flood events,
 467 calculated using the Peak Over Threshold method on a Compound Poisson
 468 Process. We proposed a simple approach to calculate a reference mean event
 469 for a given return period and its application to the stochastic model for the
 470 uprooting probability.

471 Our analysis has been carried out for one single event and returns the
472 probability of uprooting associated to characteristic flood/erosion events of
473 assigned return period. However, riparian vegetation may withstand many
474 more erosion events during its life. This suggests that the interval between
475 consecutive peak events and the ability for riparian species to recover and
476 grow in this interval play a fundamental role in the evolution of water driven
477 patterns (Bertagni et al., 2018), both from the biological and the morpholog-
478 ical point of view (Edmaier et al., 2015; Perona and Crouzy, 2018; Calvani
479 et al., 2019b). For this reason, the role of the intertime between consecutive
480 flood events and their cumulative effects should be further investigated.

481 Our results suggest that the critical erosion depth L_e and average fre-
482 quency of peak events λ_P are the key parameters to define the uprooting
483 probability of riparian vegetation in a given river basin. Yet, this study
484 confirms that long time scale interactions between river hydro-morphology
485 and riparian vegetation are fundamental to shape the riverine environment
486 (Bywater-Reyes et al., 2015). For a given hydrological regime, the mecha-
487 nisms at the base of such interactions may be key to select species according
488 to their ability to survive in water-driven environments. For instance, in-
489 vasive riparian plants can take advantage of these interactions, leading to

490 colonization of new fluvial landforms and suppression of local species, due to
491 alteration in the hydrological regime by either human impacts (Tealdi et al.,
492 2011; Coletti et al., 2017) or climate change (Serrat-Capdevila et al., 2007;
493 House et al., 2016).

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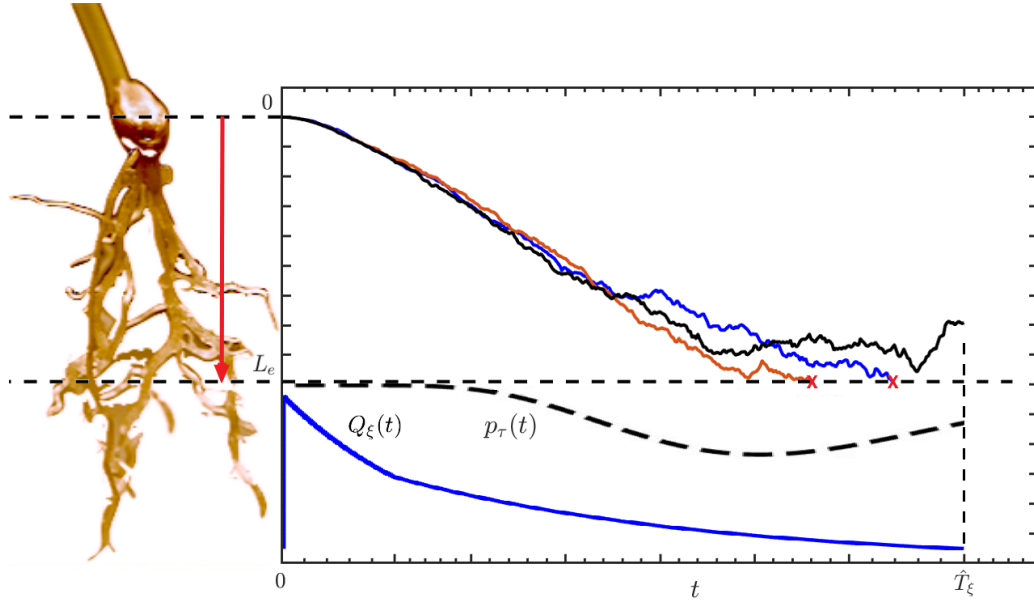


Figure 1: Illustration of the approach described by Eq. (2). The erosion rate evolves driven by flow hydrograph $Q_\xi(t)$, lasting \hat{T}_ξ , and erosion noise, g_t , so that different scouring trajectories result to a probabilistic distribution function, p_τ , of the times to uprooting. Vegetation is removed when total erosion reaches the critical erosion depth, L_e .

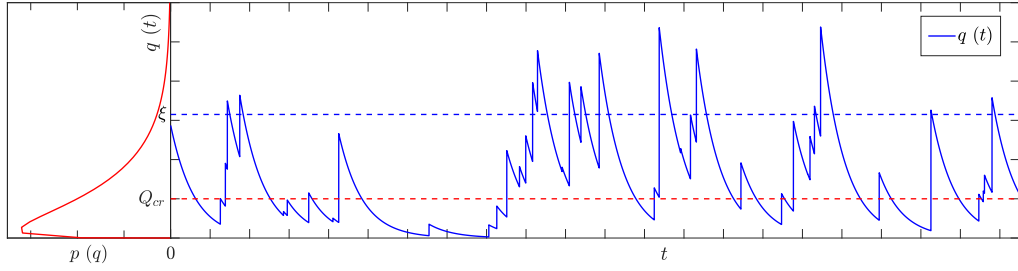


Figure 2: A sample realization of a Compound Poisson Process of flow discharge $q(t)$ (continuous blue line). Dashed blue line is the threshold ξ for extreme value analysis. Dashed red line is the critical threshold Q_{cr} for bed erosion. On the left the probabilistic distribution function $p(q)$ of flow discharge (continuous red line).

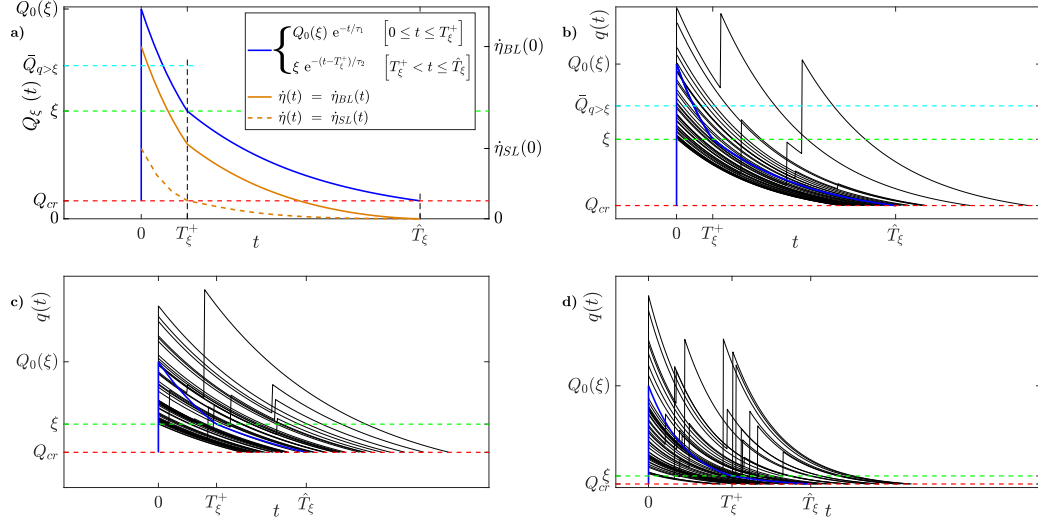


Figure 3: The reference mean event $Q_\xi(t)$ is the statistically averaged hydrograph associated to jumps above the threshold ξ . a) The reference mean event (continuous blue line) and its associated erosion rate, both in case of bedload (continuous dark-yellow line) and suspended load (dashed dark-yellow line) (see section 2.4). b) A comparison between the calculated hydrograph and some events above the threshold ξ extracted from a Compound Poisson Process. c) The reference mean event for the Small River whit $\xi=180\text{m}^3\text{s}^{-1}$ and some events taken from the CPP above such threshold. d) The reference mean event for the Large River with $\xi=550\text{m}^3\text{s}^{-1}$ and comparison to some events taken from the CPP.

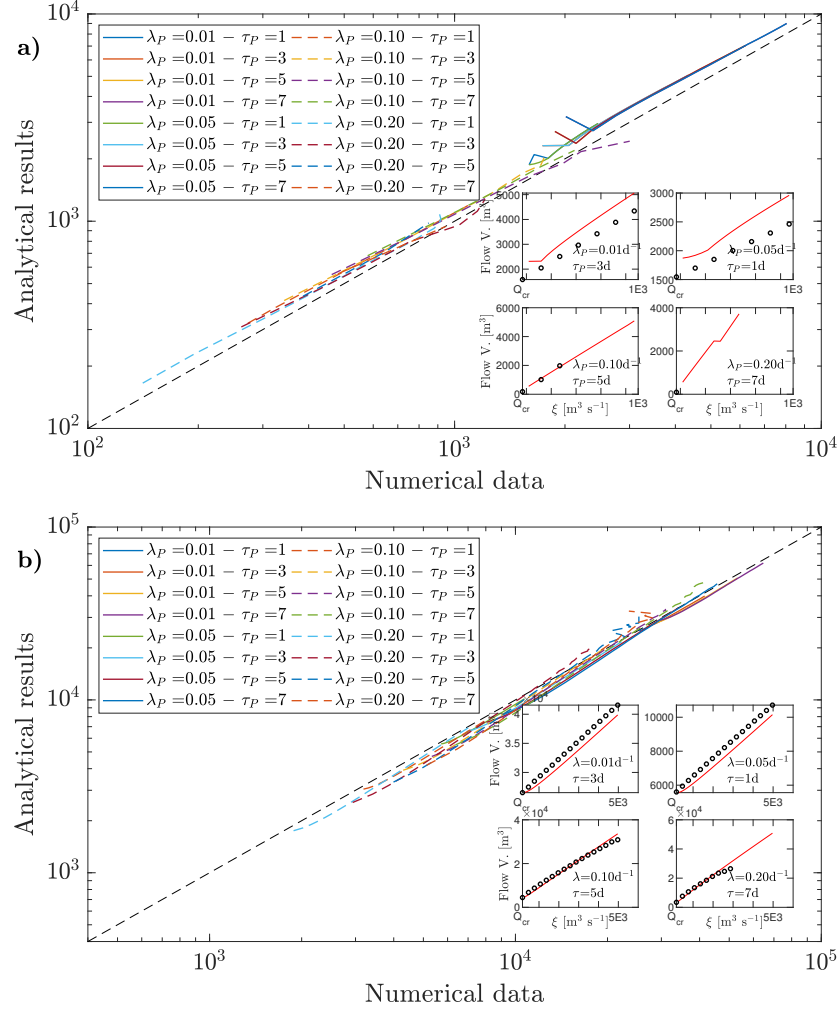


Figure 4: The flow volume comparison between the reference mean event (analytical results) and some events taken from the CPP (numerical data) for the two ideal rivers involved in the analysis. Values are in m^3 . a) The comparison for the Small River. b) The comparison for the Large River. Inset panels show the agreement for different combinations of the parameters λ_P and τ_P , according to different values of the threshold ξ .

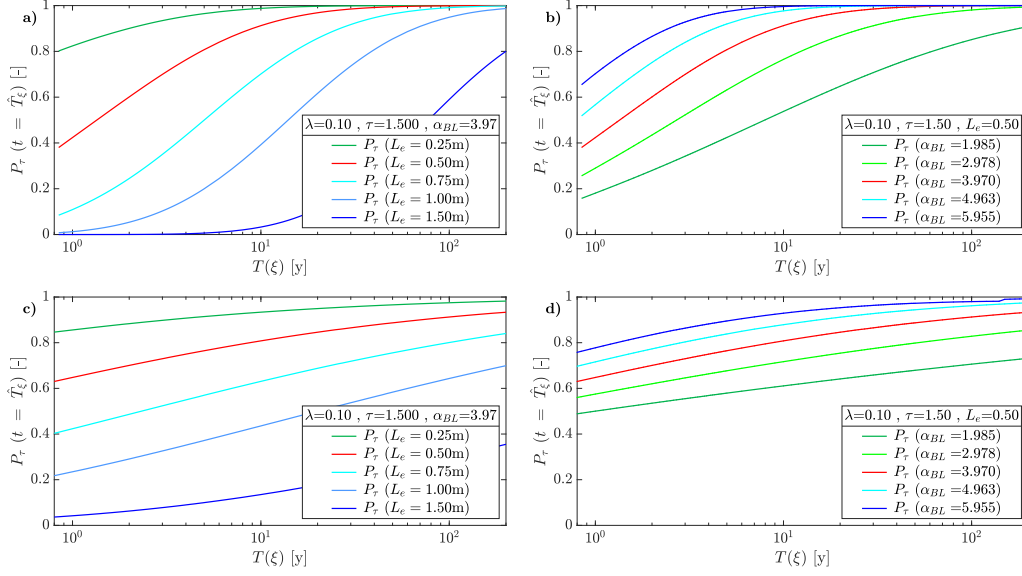


Figure 5: The uprooting probability, $P_\tau(t)$, in the Small River (panels a) and b)) and the Large River (panels c) and d)), at the end of the reference mean event ($t = \hat{T}_\xi$), according to different values of the parameters involved in Eq. (5). Values of the parameters are shown and, when not explicitly written, units are: [m] for L_e , [d^{-1}] for λ_P , and [d] for τ_P . a) and c) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the critical length of erosion L_e , for the Small River and the Large River, respectively; b) and d) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the coefficient α_{BL} in the bedload transport formula, for the Small River and the Large River, respectively.

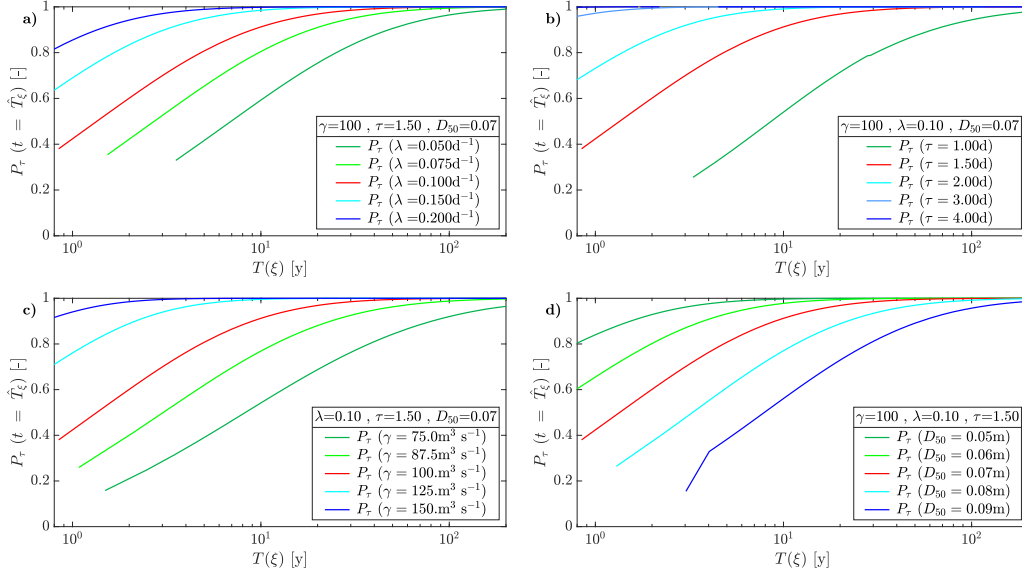


Figure 6: The uprooting probability, $P_\tau(t)$, in the Small River, at the end of the reference mean event ($t = \hat{T}_\xi$), according to different values of the parameters involved in Eq. (5). Noise in erosion process g_t is set to $0.05\text{m}^2\text{d}^{-1}$, values of the other constant parameters are shown. When not explicitly written, units are: [m] for L_e , $[\text{d}^{-1}]$ for λ_P , and [d] for τ_P . a) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean frequency of jumps λ_P ; b) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the exponential decay rate τ_P ; c) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean jump value γ_P ; d) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean grain size D_{50} .

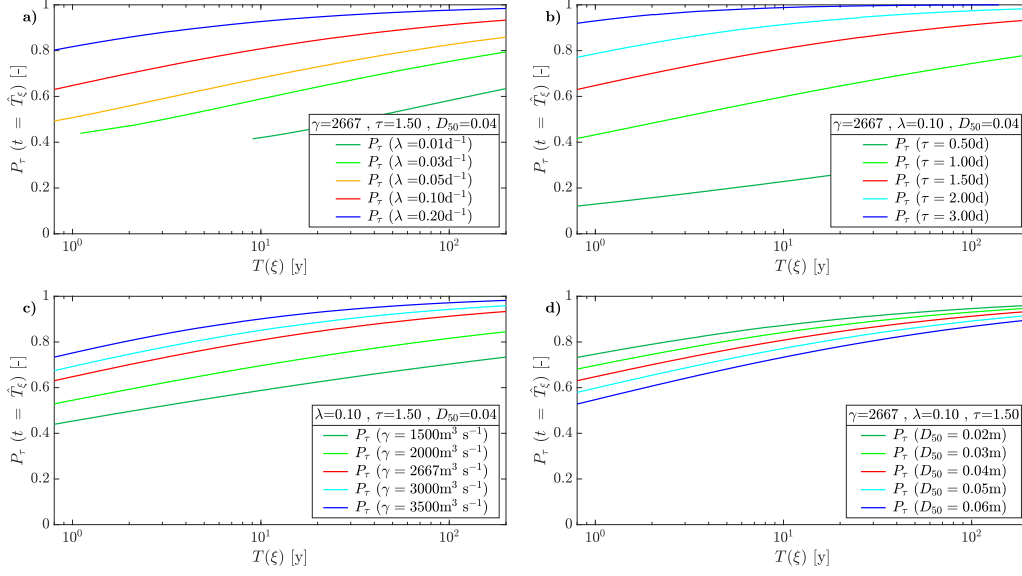


Figure 7: The uprooting probability, $P_\tau(t)$, in the Large River, at the end of the reference mean event ($t = \hat{T}_\xi$), according to different values of the parameters involved in Eq. (5). Noise in erosion process g_t is set to $0.05\text{m}^2\text{d}^{-1}$, values of the other constant parameters are shown. When not explicitly written, units are: [m] for L_e , $[\text{d}^{-1}]$ for λ_P , and [d] for τ_P . a) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean frequency of jumps λ_P ; b) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the exponential decay rate τ_P ; c) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean jump value γ_P ; d) $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ varying the mean grain size D_{50} .

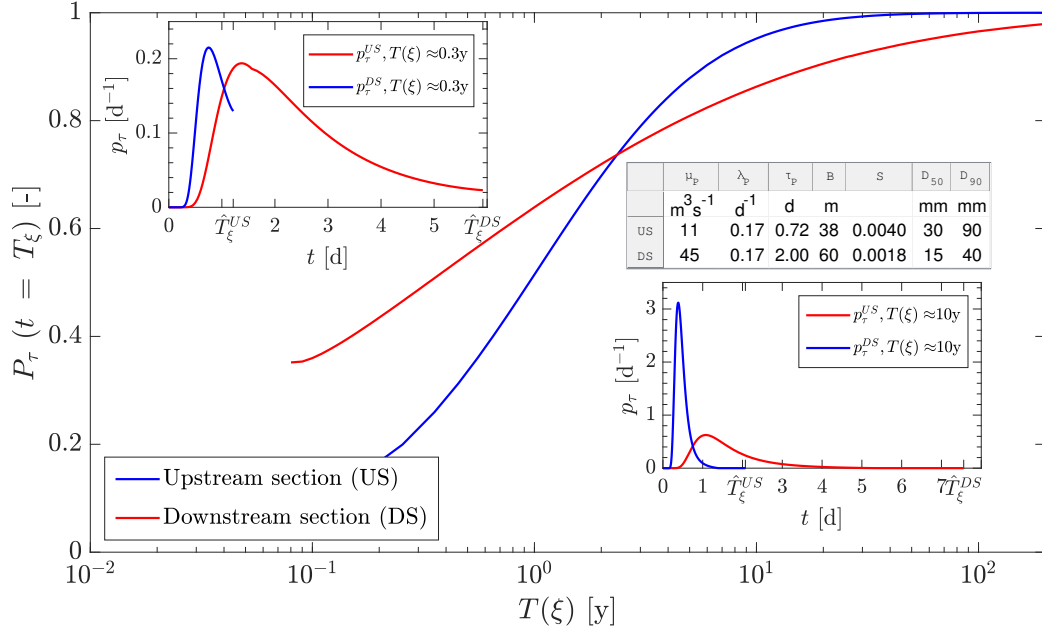


Figure 8: The uprooting probability, $P_\tau(t)$, at varying cross section. Hydro-morphological parameters are reported in the inset table. Blue line is for the upstream cross section (US), red line for the downstream one (DS). Inset panels show the probability distributions functions, p_τ , for short (e.g., $T(\xi) \approx 0.3y$) and long (e.g., $T(\xi) \approx 10y$) return periods.

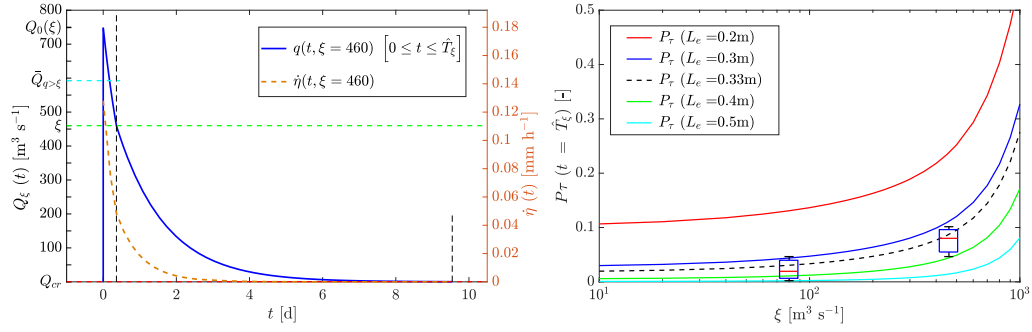


Figure 9: The uprooting probability $P_\tau(t)$ in the Santa Maria River, Arizona (USA) and comparison to the data calculated by Bywater-Reyes et al. (2015). a) The reference mean event $Q_\xi(t)$ for 10y return period and its associated erosion rate $\dot{\eta}_{SL}(t)$ due to suspended load. b) Comparison of $P_\tau(t = \hat{T}_\xi)$ with different L_e . Boxplots are the probability of uprooting calculated with measured data by Bywater-Reyes et al. (2015) for 2 and 10y return periods.

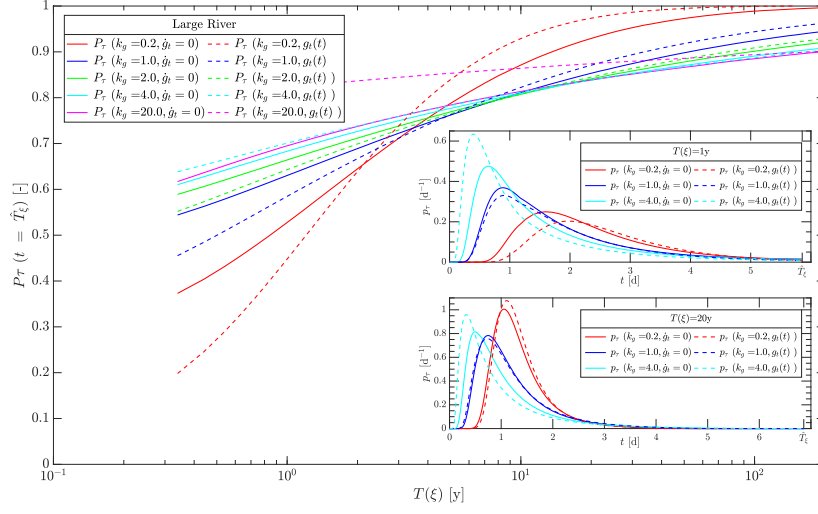


Figure 10: Graphical comparison of uprooting probability $P_\tau(t = \hat{T}_\xi)$ versus return period $T(\xi)$ for different values of the time-varying noise $g_t(t)$ (Eq. (3)) and its integral mean over the duration \hat{T}_ξ for different values of the coefficient k_g of the *sediment mixing length* l_s (Eq. (4)) in the Large River. Continuous lines are for the uprooting probability with constant g_t , dashed lines are for the uprooting probability with time-varying g_t . In the inset panels the probability distribution functions, p_τ , corresponding to the reference mean event of two different return period (i.e., $T(\xi) = 1y$ and $T(\xi) = 20y$) for different values of the coefficient k_g .